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RESEARCH ARTICLE

Contracting Strategy for Consumers With Distributed Energy Resources in the Liberalized Electricity Market

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ABSTRACT The rapid growth of distributed energy resources (DERs) and the new trends related to the electricity market can represent economic advantages for consumers; nevertheless, these trends can bring economic risks, such as high prices when contracting, and the inability to forecast information related to offers and demand. A contracting strategy is essential to minimize possible financial losses due to consumer exposure in the liberalized electricity market. This paper proposes a contracting strategy based on consumption forecasting and a pricing methodology to optimize the contract portfolio for consumers with DERs. A consumer with a photovoltaic system and battery storage system has been considered to model the contracting strategy through a mathematical programming approach developed in four stages; the first and second stages are nonlinear programming problems, the third stage is linear programming problem, and the last stage is mixed-integer linear programming problem. The results of the case study, considering a real consumer with and without DERs, show that the strategy successfully minimized consumer exposure in the electricity market, since with operation of DERs was reduced by 45.8% the energy consumption from the main grid and by 49.7% the need for contracting, optimizing the average price of the contract portfolio and making it possible to determine an optimal contracting strategy.

INDEX TERMS Contracting, electricity consumers, liberalized electricity market, pricing.

NOMENCLATURE

A. INDICES AND SETS

ae	Indices of batteries.
m	Indices of months.
rd	Indices of representative days.
t	Indices of hours.
y	Indices of years.
AE	Set of batteries.
M	Set of months.
RD	Set of representative days.
T	Set of hours.
Y	Set of years.

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B. PARAMETERS

α_{ae}	Battery efficiency.
APC_y	Average price contracted per year [R$/MWh]
$CI_{m,y}$	Monthly consumption index per year
CPC	Current price [R$/MWh]
$C^{FUTF}_{m,y}$	Monthly future contract per year (flexibility computation) [MWh]
$C^{EXTF}_{m,y}$	Monthly existing contract per year (flexibility computation) [MWh]
$C^{FUTS}_{m,y}$	Monthly future contract per year (seasonal computation) [MWh]
$C^{EXTS}_{m,y}$	Monthly existing contract per year (seasonal computation) [MWh]
ECC_y	Expected average consumption per year [MW]
FEP_y	Future energy price per year [R$/MWh]

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$\overline{Flex}$	Upper flexibility limit [%]
$\underline{Flex}$	Lower flexibility limit [%]
HM_m	Hours at month
L	Maximization/minimization factor
LI_y	Load Index per year
Lim_y^{Me}	Measure limit [%]
MAX_{ae}^{SE}	Maximum energy storage [MWh]
MAX_{ae}^{SP}	Maximum power of injection/extraction [MW]
$PD_{t,rd}^{RD}$	Power demand at hour of representative days
$PDM_{m,y}^{FS}$	Monthly power demand per year – flexibility/seasonal computation [MWh]
PPV_y	Photovoltaic power installed per year [MWp]
PR_{rd}	Probability at representative day
$SEB0_{ae}$	Initial stored energy of battery [MWh]
$SI_{t,rd}$	Statistic index of photovoltaic generation at hour of the representative day
ST_y	Strategy per year
$TEC_{m,y}$	Total monthly energy contracted per year [MWh]

C. VARIABLES

APF_y	Future price average per year [R$/MWh]
$C_{m,y}^{FUT}$	Monthly future contract per year [MWh]
$C_{m,y}^{EXT}$	Monthly existing contract per year [MWh]
$C_{m,y}^{TOTAL}$	Total monthly contract per year [MWh]
$C_{m,y}^{TOTALF}$	Monthly total contract per year (flexibility computation) [MWh]
$C_{m,y}^{TOTALS}$	Monthly total contract per year (seasonal computation) [MWh]
EC_y	Expected average consumption per year [MW]
$EE_{t,y,rd}$	Excess of power at hour per year of representative day [MW]
EX_y^Y	Annual average exposure [MW]
$Flex_{m,y}$	Monthly flexibility per year [%]
$Flexc_{m,y}$	Monthly contract and measure factor per year [%]
$PD_{t,y,rd}$	Power demand at hour per year of representative day [MW]
$PDM_{m,y}$	Monthly power demand per year [MWh]
$PB_{t,y,rd,ae}$	Active power of injection/extraction at hour per year of representative day [MW]
$SAZO_{m,y}$	Monthly sazonality per year [%]
$SEB_{t,y,rd,ae}$	Stored energy in the battery at hour per year of representative day [MW]
TEF_y	Future average contract per year [MW]
TEC_y^Y	Currente average contract per year [MW]
VC_y	Contract value per year [R$]
$w_{m,y}^1, w_{m,y}^2, w_{m,y}^3$	Monthly linearization steps per year [binary]

I. INTRODUCTION

The effort to mitigate the energy dependence of petroleum derivatives has led to the accelerated advance of distributed energy resources (DERs), such as photovoltaic generation units (PVs), energy storage, and wind plants [1]. To suitably integrate DERs into the electrical system, certain aspects related to the electricity market must be managed to guarantee the DERs' optimal operation in electrical systems. There are two different electrical markets: the wholesale electricity market and the local market. In the wholesale electricity market, the players make the energy transaction with the main grid through a central operator. In the local electricity market, the players have the ability to carry out energy transactions in a decentralized manner, without the coordination of an intermediary operator [2]. Moreover, in the wholesale electricity market, energy transactions can occur with and without the consumer's participation (choosing offers or making decisions in the electricity market). Nevertheless, and depending on the regulatory framework of each country, consumers can participate in the wholesale energy market if the power demand is large enough. For instance, Brazil must have been more than 1500 kW [3]; thus, in such cases, it is possible for consumers to participate in a liberalized electricity market. On the other hand, if the power demand is less than the minimum power required, the energy transactions occur between large suppliers and retailers, and then the electricity is offered and distributed to the consumers in the retail electricity market [4]. The deregulation of the retail electricity market has leveraged a transition from captive consumers to liberalized consumers [5]. Captive consumers are needed to provide a secure system of negotiation, and therefore, it is impossible for them to choose their electricity suppliers, tariffs, and schemes of contracting, lessening the possibility of receiving economic benefits [6]. In contrast, in the case of a liberalized market, consumers can choose their electricity suppliers [4]. The main characteristics of the liberalized electricity market are that contracting can be short, medium, and long-term and that, to participate in contracting, the minimum requirement of the power demand of the consumers will be established by the regulatory framework of each country [4]. Moreover, depending on the regulatory framework of each country, renewable energy resources must be used to meet the demand of the consumers, which can minimize the energy cost to the buyers [4]. The fact that in the liberalized market the consumers can select their electricity supplier provides flexibility to the energy transactions and can result in economic benefits to the buyers [7]. Nevertheless, the consumers are exposed to the variability of prices and uncertain demand; hence, the suppliers and consumers must have knowledge of all possible risks in order to create strategies to avoid them[8].

Because of its potential to improve economic benefits to electricity consumers, interest in the liberalized electricity market has been increasing in the last few years [6], [9], [10]. The authors in [11] formulated a bilevel programming model for a generation company's long-term generation capacity investment decision. The bilevel formulation considered the uncertainty regarding the investments; in the upper level, the objective is to maximize the profits of the generation companies. The lower level consists of a liberalized market that includes conjectured price variations. The novelty of this proposal is that it focuses on the stochastic convex formulation for the bilevel problem, taking into account uncertainties related to investment decisions of the competition in the electricity market. Nevertheless, the diversification of the portfolio considering renewable energy is not added in the mathematical model proposed. Criteria of seasonality and flexibility can improve the electricity transaction in the liberalized market. Seasonality refers to the definition of the amount of energy contracted annually in monthly volumes, according to a delivery profile previously validated by the parties [12]. Regarding flexibility, contractual flexibility allows the consumer to have flexibility in the variation of the load consumption related to the amount of energy contracted in a given month [12]. A mathematical optimization model aiming to minimize the energy cost to serve the demand of consumers of a liberalized market has been proposed in [12], in which the main contribution is that the mathematical representation takes into account constraints related to seasonality and flexibility for consumers who want to achieve a competitive price for their power demand. Even though the proposal is significantly novel, the mathematical representation does not consider energy from DERs in the portfolio offered to the consumers. Renewable energy generation diversifies the portfolio of the liberalized electricity market; hence, it is a trend that is currently receiving particular attention [13], [14]. The authors in [15] developed a statistical mixed distribution model to forecast errors related to wind energy generation. The main objective of this proposal is focused on minimizing the penalties regarding the errors of wind generation, aiming to improve the cost of renewable energy in the liberalized market. Notwithstanding the interesting contribution in the area of forecasting renewable generation, criteria related to seasonality and flexibility in order to lessen the risks related to the uncertainty of offers and demand have not been considered. A bilevel stochastic programming model for a liberalized electricity market's short-term decision-making strategy has been proposed in [6]. In this proposal, several retailers and aggregators compete to purchase renewable energy from several DER producers, aiming to minimize their energy cost. Hence, at the upper level, the aggregators and retailers minimize their energy cost, while at the lower level, the DERs receive price signals from the retailers and intend to maximize their revenues. Moreover, the major novelty is that the uncertain nature related to DERs generation, electricity demand, and energy prices has been taken into account.

Most of the studies encountered in the literature review have focused on strategies for long-term investment decisions aiming to minimize the risks associated with the uncertainties of prices and power demand in the liberalized electricity market [7], [11]. Moreover, several proposals are devoted to short-term decision-making models to maximize sellers' revenues or to minimize buyers' cost in a liberalized electricity market environment [6], [16], [17]. Some approaches consider the renewable energy generation, aiming to diversify their portfolio and consequently improve the transactions made in the liberalized electricity market for both buyers and sellers [6], [18], [19], [16]. Nevertheless, the participation of the DERs in the retail electricity market is not considered highly competitive, because, in some countries, the DERs are considered small producers and are limited by, for instance, the lack of a contracting strategy to achieve optimal and competitive participation in the liberalized electricity market. Table 1 provide a summary of the research addressing this area. To the best of the authors' knowledge, none of the preceding works has focused on the development of a contracting strategy considering criteria such as seasonality and flexibility in a liberalized electricity market environment with the participation of DERs and consumers.

To address this research gap, this paper proposes a novel contracting strategy that considers consumption forecasting and pricing methodology for contract portfolio optimization for consumers with DERs. Therefore, the main objective of this paper is to find an optimal contracting strategy that guarantees both DERs and consumers an ideal average price of electricity, protecting them from risks associated with uncertainties of the variability of electricity prices and power demand. This paper contributes to the existing literature by proposing:

- A mathematical tool that helps liberalized consumers (with or without DERs) to develop their contracting strategies of electrical energy in different periods and integrated them into the energy management system;
- An optimization model that represents a consumer's adequate operation, integrated with photovoltaic and battery storage systems, aiming to enable the battery to be charged in periods of high PV generation and to provide the battery with energy (to serve conventional loads) in periods of low PV generation; and
- A framework that defines the average price to be contracted, meeting the expectations and financial strategies of a consumer, and considering a contractual amount, seasonality, and flexibility.

II. MATHEMATICAL PROGRAMMING APPROACH

The contracting strategy is the most important step for consumer success in the liberalized electricity market. Nevertheless, as technologies advance and new consumption profiles emerge, due to the DERs insertion, the consumer's challenge, to correctly identify the real necessity of its electricity consumption becomes more complex.

Furthermore, the volatility of electricity prices can also represent challenges for consumers; hence, strategies that consider these issues and offer solutions became necessary. The mathematical programming approach develops in four

TABLE 1. Main works related to liberalized market for consumers with distributed energy resources.

References	Minimize the exposition of the consumers in the electricity market	Contracting strategy based on consumption forecasting	Integration with RESs	Criteria of seasonality and flexibility
[4]	✓	✓		
[6]	✓		✓	
[10]	✓		✓	
[12]	✓			✓
[13]			✓	
[14]			✓	
[15]	✓		✓	
[16]	✓	✓		
[18]	✓		✓	
This work	✓	✓	✓	✓

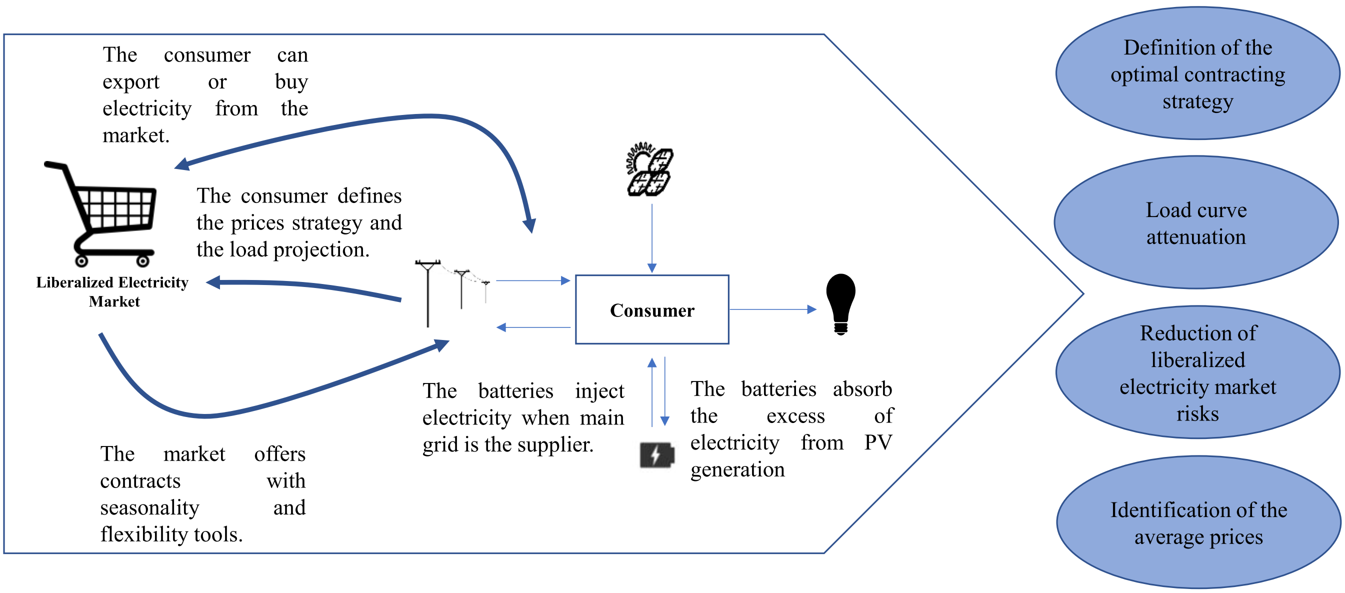

FIGURE 1. Contracting strategy proposed for the liberalized electricity market.

stages; first and second stages are nonlinear programming problems, the third stage is linear programming problem, and the last stage is mixed-integer linear programming problem. The main optimization objective is to reduce consumer exposure to the liberalized electricity market for the next years and, consequently, mitigate the risks. Figure 1 shows the contracting strategy proposed.

A. PROPOSED METHODOLOGY

The methodology proposed in this paper, integrating four different stages, is represented in Figure 2. Note that each stage provides data for the next stage, and all contribute to the flexibility application modelling in the fourth stage. Moreover, this modeling offers the consumer the possibility of using each stage separately from the others, calculating the results separately, depending on the user's necessity. It is important to observe that, in this case, the consumer needs to have the parameters of each stage, provided by different sources such as historical data or market information.

The variable $PDM_{m,y}$ of the first stage is used in the third and fourth as the parameter $PDM^{FS}_{m,y}$, representing the monthly expected consumption. The variable EC_y, which represents the annual expected consumption, is used in the second stage as the parameter ECC_y, resulting from the electricity balance curve.

This last parameter is required by the second stage to calculate the future flat contract amount, $C^{FUT}_{m,y}$, and the average price, APF_y, of the contracts portfolio. To convert from a flat to a seasonal contract, the third stage uses the future flat contract data from the second stage as the parameter $C^{FUTS}_{m,y}$. Finally, the flexibility application in the fourth stage requires the seasonalized contract amount calculated in the third stage, called the parameter $C^{FUTF}_{m,y}$.

B. FIRST STAGE – OPERATION MODELING FOR CONSUMERS WITH DERs

The first stage of the mathematical modeling involves finding the optimal operation mode for consumers with DERs, which means obtaining the electricity balance curve and identifying the expected amount of power consumption from the main grid. The objective function is focused on the minimization of exposure to liberalized electricity market,

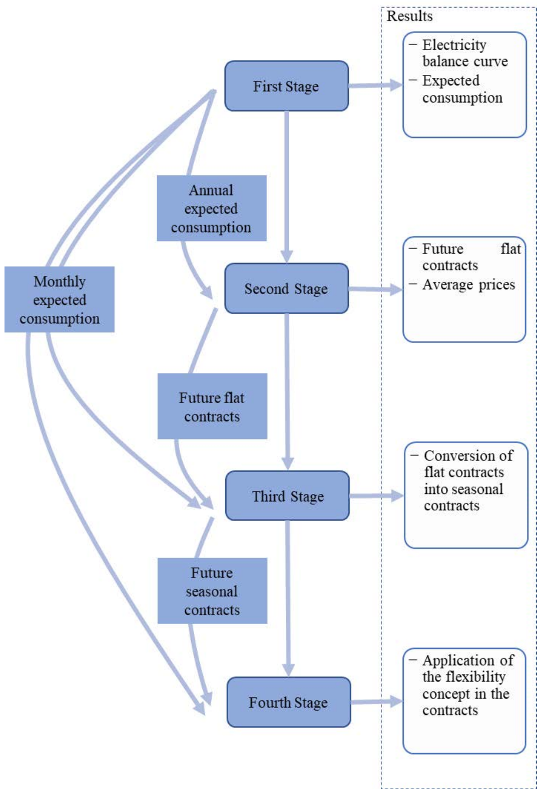

FIGURE 2. **Proposed methodology flowchart.**

as indicated by (1).

$$min\left\{\sum_{y\in Y} EC_y\right\} \tag{1}$$

Based on historical data regarding consumption and generation, similar performances are grouped together, considering each time period. This process, called clustering, uses algorithms with different methods to find similarities, such as Euclidian or probability distances, or other metrics [20]. As a result, the clustering process shows a reduced number of clusters that represent the operational condition of the system [21]. The average value of all the observations allocated in a cluster represents the centroid and the number of observations, and consequently, the probability of each scenario is obtained. From this approach, the authors in [22] introduced the representative periods concept, which means that each cluster represents similar periods.

The application of this concept in the proposed mathematical modeling was based on the fact that the use of representative periods provides less complexity in the modeling and less computational effort, since it works with a smaller quantity of data without losing the characteristics of consumption and generation. These representative periods were referred to here as representative days. The expected consumption EC_y is formulated by mathematical representation of the power consumption from the main grid, written in terms of the product of the power demand in hours per year of the representative day ($PD_{t,y,rd}$) with the probability (PR_{rd}), which represents a combination of the individual consumption and photovoltaic generation probabilities, as shown by (2). The set RD is composed by the number of representative days and the set T consists of 24 hours of a day.

$$EC_y = \left\{\sum_{rd\in RD}\sum_{t\in T}\frac{PD_{t,y,rd} * PR_{rd}}{24}\right\} \quad \forall y\epsilon Y \tag{2}$$

The power balance depends on the internal load and power generation forecasting of each representative day, as shown in (3).

$$\begin{aligned} PD_{t,y,rd} &= PD^{RD}_{t,rd} * \left(1 + LI_y\right) - PPV_y * SI_{t,rd} \\ &\quad + \sum_{ae\in AE} PB_{t,y,rd,ae} - EE_{t,y,rd} \\ &\quad \forall t\epsilon T, \quad \forall y\epsilon Y, \ \forall rd\epsilon RD \end{aligned} \tag{3}$$

Eq. (3) is formed according to four installments. The internal power demand is a product of the internal power demand of the representative day ($PD^{RD}_{t,rd}$) with the consumer's perspective for future internal load, using the factor LI_y for each year of the set Y. The photovoltaic power installment makes use of the generation profile represented by $SI_{t,rd}$ associated with consumer's perspective on the future installed power generation (PPV_y). The battery power, $PB_{t,y,rd,ae}$ represents the injection or extraction of power from batteries, considering the number of batteries systems of the set AE. Lastly, the excess of power $EE_{t,y,rd}$ must respect the constraint in (4).

$$\begin{aligned} EE_{t,y,rd} \geq \min\Bigg(&0, PD^{RD}_{t,rd} * \left(1 + LI_y\right) - PPV_y * SI_{t,rd} \\ &+ \sum_{ae\in AE} PB_{t,y,rd,ae}\Bigg) \quad \forall t\epsilon T, \ \forall y\epsilon Y, \\ \forall rd\epsilon RD \end{aligned} \tag{4}$$

This expression guarantees that an excess of power occurs only when the photovoltaic generation is greater than the internal load. Therefore, the main grid is not used to charge the batteries. The consumption per year is shown in (2). For the next stages, the consumption per month is required, as shown in (5).

$$PDM_{m,y} = \left(EC_y * 8760 * CI_{m,y}\right) \quad \forall y\epsilon Y, \ \forall m\epsilon M \tag{5}$$

Note that, in (5), the variable $PDM_{m,y}$ is given in MWh. Therefore, the annual average expected consumption EC_y must be multiplied by the total hours of a year and normalized by the factor $CI_{m,y}$ to calculate the curve of consumption per month of each year. The batteries are charged only when the balance results in an excess of generation and discharging when the generation capacity is low. This process is represented by (6)–(11).

$$\begin{aligned} SEB_{t,y,rd,ae} &= SEB0_{ae} + \alpha_{ae} * PB_{t,y,rd,ae} \\ &\quad \forall t\epsilon T/t = 1, \quad \forall y\epsilon Y, \ \forall rd\epsilon RD, \\ &\quad \forall ae\epsilon AE \end{aligned} \tag{6}$$

$$SEB_{t,y,rd,ae} = SEB_{t-1,y,rd,ae} + \alpha_{ae} * PB_{t,y,rd,ae}$$

$$\forall t\epsilon T/t>1, \quad \forall y\epsilon Y, \forall rd\epsilon RD, \forall ae\epsilon AE \tag{7}$$

$$-MAX_{ae}^{SP} \leq PB_{t,y,rd,ae} \leq MAX_{ae}^{SP} \quad \forall t\epsilon T, \quad \forall y\epsilon Y, \forall rd\epsilon RD, \forall ae\epsilon AE \tag{8}$$

$$0 \leq SEB_{t,y,rd,ae} \leq MAX_{ae}^{SE} \quad \forall t\epsilon T, \quad \forall y\epsilon Y, \forall rd\epsilon RD, \forall ae\epsilon AE \tag{9}$$

$$\sum_{t\in T} PB_{t,y,rd,ae} = 0 \quad \forall y\epsilon Y, \forall rd\epsilon RD, \forall ae\epsilon AE \tag{10}$$

$$\sum_{ae\in AE} PB_{t,y,rd,ae} \leq EE_{t,y,rd} \quad \forall t\epsilon T, \forall y\epsilon Y, \forall rd\epsilon RD \tag{11}$$

The expressions in (6) and (7) represent the energy stored in the battery at each time interval for each year of each representative day. Specifically, (6) represents the battery charging at the first time interval, and (7) indicates the battery charging at others time intervals. The limit of the battery power and of the capacity for energy storage in the battery are represented by (8) and (9), respectively. The expression (10) ensures that, on the same day of operation, the batteries' energy sum is null. The equation (11) guarantees that the power in the battery is less than the excess of power.

Note that, model (1) – (11) is a nonlinear programming problem by the nonlinearity given by (4). The nonlinearity is introduced in the mathematical formulation by the *min* function in expression (4).

C. SECOND STAGE – COMMERCIAL MODELING FOR CONSUMERS WITH DERS

This stage is responsible for finding the average prices and the total amount of electricity that must be contracted per year, according to the consumption expected from the main grid, calculated in the first stage, and the price strategy defined by the consumer. The objective function of the second stage, represented by (12), minimizes the consumer's exposure in the electricity market.

$$min \left\{ \sum_{y\in Y} EX_y^Y \right\} \tag{12}$$

The consumer's yearly contract balance can be obtained by (13), complemented by (14).

$$ECC_y - TEC_y^Y - TEF_y = EX_y^Y \quad \forall y\epsilon Y \tag{13}$$

$$TEC_y^Y = \frac{\left(\sum_{m\in M} TEC_{m,y}\right)}{8760} \quad \forall y\epsilon Y \tag{14}$$

Note that, (13) uses the total amount of current and future contracts and the total consumption calculated in the first stage. The expression (14) utilizes the sum of the monthly current contract parameter, $TEC_{m,y}$, given in MWh, considering the number of months in a year, provided by the consumer, representing the annual average of the electricity contracted.

As the objective function in (12) is to find the smallest amount of exposure in the year, the objective in (13) maximizes future contracting as much as possible according to the strategy in (15)–(18).

$$APF_y = \frac{\left(\left(TEC_y^Y * APC_y\right) + \left(TEF_y * FEP_y\right)\right)}{TEC_y^Y + TEF_y} \quad \forall y\epsilon Y \tag{15}$$

$$APF_y \leq \left(1 - ST_y\right) * CPC \quad \forall y\epsilon Y/y=1 \tag{16}$$

$$APF_y \leq \left(1 - ST_y\right) * APF_{y-1} \quad \forall y\epsilon Y/y>1 \tag{17}$$

$$TEF_y \leq \max\left(0, EC_y - TEC_y^Y\right) \quad \forall y\epsilon Y \tag{18}$$

The expression in (15) represents the annual average price of the contracts, considering the currents and the future electricity amounts and the prices of the contracts. The price strategy depends on the consumer, who must indicate, each year, the expected price reduction, as shown in (16). Hence, for the first year, the base electricity price is the current value, CPC, and the term ST_y indicates the reduction expectation in the same period. For the following years, the base price is the same as that of the previous year, and the expression in (17) represents the average value for the second year. The limitation for future contracting is given by (18), which indicates an electricity acquisition only if the amount of the current contract is less than the expected consumption.

Note that, model (12)–(18) is a nonlinear programming problem due to the multiplication of variables in (15) and the use of the *max* function in (18).

The next stages, require a monthly representation of the current and future contracts, as represented by (19) and (20), respectively.

$$C_{m,y}^{EXT} = TEC_{m,y} * HM_m \quad \forall y\epsilon Y, \forall m\epsilon M \tag{19}$$

$$C_{m,y}^{FUT} = TEF_y * HM_m \quad \forall y\epsilon Y, \forall m\epsilon M \tag{20}$$

The total of the monthly contracts per year is given by (21).

$$C_{m,y}^{TOTAL} = C_{m,y}^{EXT} + C_{m,y}^{FUT} \quad \forall y\epsilon Y, \forall m\epsilon M \tag{21}$$

D. THIRD STAGE – SEASONAL CONTRACT MODELING

The third stage of this modeling focuses on transforming the flat characteristic of TEF_y represented by (13) into a seasonal contract. The consumer can share the total amount of the contract in different values per month, according to the limits of seasonality agreed upon by the supplier. This contract's requirement realizes the balance of deficit and excess of electricity; thus, through the consumer's projection of the monthly consumption, in months when the contract is greater than the consumption, the consumer can allocate less electricity than stated in the contract. If the contract provides for less than the consumption, the consumer can allocate more electricity, but the annual amount cannot be modified. Consequently, the curve of the contract is closer to the consumption curve.

The objective function in (22) minimizes the difference between the yearly consumption and the total electricity contract represented by (23).

$$min \left\{ \sum_{y \in Y} PDM_{m,y}^{FS} - \sum_{y \in Y} C_{m,y}^{TOTALS} \right\} \quad (22)$$

Note that, $PDM_{m,y}$ is a variable from first stage, and now is a parameter for this stage and for stage four, called $PDM_{m,y}^{FS}$.

$$C_{m,y}^{TOTALS} = C_{m,y}^{EXTS} + C_{m,y}^{FUTS} * \left(1 + SAZO_{m,y}\right) \quad \forall m \epsilon M, \quad \forall y \epsilon Y \quad (23)$$

This expression is formed using the amount of the current and future contracts and the term $SAZO_{m,y}$ represents the optimal seasonality per month. It is important to highlight that, in this stage, $C_{m,y}^{EXTS}$ and $C_{m,y}^{FUTS}$ are parameters, although they were variables in the second stage ($C_{m,y}^{EXT}$, $C_{m,y}^{FUT}$). An important characteristic of the seasonal contracts is given by (24).

$$\sum_{m \in M} C_{m,y}^{FUTS} * \left(1 + SAZO_{m,y}\right) = \sum_{m \in M} C_{m,y}^{FUTS} \quad \forall y \epsilon Y \quad (24)$$

In this expression the variable $SAZO_{m,y}$ is adjustable aiming to ensure that the total annual amount of the contract is guaranteed. The total seasonal contract must respect the limitations represented by (25) and (26).

$$\begin{aligned} &C_{m,y}^{EXTS} + C_{m,y}^{FUTS} * \left(1 + SAZO_{m,y}\right) \\ &\quad \leq max \left(PDM_{m,y}^{FS}, \left(C_{m,y}^{EXTS} + C_{m,y}^{FUTS}\right)\right) \\ &\quad \forall m \epsilon M, \forall y \epsilon Y \end{aligned} \quad (25)$$

$$\begin{aligned} &C_{m,y}^{EXTS} + C_{m,y}^{FUTS} * \left(1 + SAZO_{m,y}\right) \\ &\quad \geq min \left(PDM_{m,y}^{FS}, \left(C_{m,y}^{EXTS} + C_{m,y}^{FUTS}\right)\right) \\ &\quad \forall m \epsilon M, \ \forall y \epsilon Y \end{aligned} \quad (26)$$

The expressions above guarantee that the amount of the total seasonal contract will be between the power demand and the total amount of electricity of the contracts without seasonality. It avoids excess or deficit of electricity in each month.

Note that, model (22)–(26) is a linear programming model.

E. FOURTH STAGE – CONTRACT FLEXIBILITY MODELING

The fourth stage of the mathematical modeling uses the seasonal contract calculated in the third stage ($C_{m,y}^{TOTALS}$), referred to here as $C_{m,y}^{TOTALF}$, and applies the concept of flexibility. Once the consumer has a contract closer to the consumption curve expectation, the flexibility calculation is a contractual requirement that realizes the adjustment each month, absorbing the behaviors not expected of the consumption.

The objective of this stage is to minimize, each year, the difference between the consumption realized and the total seasonal contract with flexibilities. Hence, the expression in (27) represents the objective function.

$$min \left\{ \sum_{y \in Y} PDM_{m,y}^{FS} - \sum_{y \in Y} C_{m,y}^{TOTALF} \right\} \quad (27)$$

The flexibility calculation is represented by (28) and (29).

$$Flexc_{m,y} = \frac{\left(C_{m,y}^{FUTF} - PDM_{m,y}^{FS} * Lim_y^{Me}\right)}{C_{m,y}^{FUTF}}, \quad \forall m \epsilon M, \quad \forall y \epsilon Y \quad (28)$$

$$Flex_{m,y} = \begin{cases} Flexc_{m,y} & \underline{Flex} < Flexc_{m,y} < \overline{Flex} \\ \overline{Flex} & Flexc_{m,y} \geq \overline{Flex} \\ \underline{Flex} & Flexc_{m,y} \leq \underline{Flex} \end{cases} \quad \forall m \epsilon M, \quad \forall y \epsilon Y \quad (29)$$

In (28), the term $Flexc_{m,y}$ corresponds to the monthly proportionality of future contracts and the consumption. Note that the parameter Lim_y^{Me} limits the value of the consumption, corresponding to the relation between the amount of future contracts and the consumption in a year. This ensures the correct application of the flexibility concept, avoiding the use of the maximum or minimum flexibility each month. Thus, expression (29) represents the flexibility that can be applied, observing the possible upper ($\overline{Flex}$) and lower ($\underline{Flex}$) limits indicated by the consumer. In this case, the flexibility can only be the maximum if the $Flexc_{m,y}$ is greater than the superior limit, or the minimum if less than the inferior limit.

The expression in (29) represents the calculation of flexibility considering its maximum and minimum limits. The linearization of this system is given by (30)–(33).

$$Flex_{m,y} = -Flexc_{m,y} * w_{m,y}^1 - \underline{Flex} * w_{m,y}^2 + \overline{Flex} * w_{m,y}^3 \quad \forall m \epsilon M, \quad \forall y \epsilon Y \quad (30)$$

$$\left(-L * w_{m,y}^3 + \overline{Flex} * w_{m,y}^2 - \underline{Flex} * w_{m,y}^1\right) \leq Flexc_{m,y} \quad \forall m \epsilon M, \forall y \epsilon Y \quad (31)$$

$$Flexc_{m,y} \leq \left(\overline{Flex} * w_{m,y}^1 - \underline{Flex} * w_{m,y}^3 + L * w_{m,y}^2\right) \quad \forall m \epsilon M, \quad \forall y \epsilon Y \quad (32)$$

$$w_{m,y}^1 + w_{m,y}^2 + w_{m,y}^3 = 1 \quad \forall m \epsilon M, \ \forall y \epsilon Y \quad (33)$$

Moreover, it is possible to observe in (30) that the flexibility depends on the three binary variables ($w_{m,y}^1$, $w_{m,y}^2$, $w_{m,y}^3$) whose sum must be the unit value, as shown in (33). Consequently, the expressions in (31) and (32) represent the tests of the conditions, where the parameter L is a big enough number, representing the possibility of $Flexc_{m,y}$ being greater or smaller than the specified limits of flexibility.

The total amount of the contracts applying the flexibility requirement in each month is given by (34).

$$C_{m,y}^{TOTALF} = C_{m,y}^{EXTF} + C_{m,y}^{FUTF} * \left(1 + Flex_{m,y}\right) \quad \forall m \epsilon M, \quad \forall y \epsilon Y \quad (34)$$

The last equation of this modeling represents the monthly surplus or deficit of the contracts.

$$C_{m,y}^{TOTALF} + EEF_{m,y} \leq PDM_{m,y}^{FS} \quad \forall m \epsilon M, \ \forall y \epsilon Y \quad (35)$$

TABLE 2. Probabilites.

	Day 1	Day 2	Day 3
Consumption	28.0%	34.0%	38.0%
Solar Radiation Index	23.0%	34.0%	42.0%

TABLE 3. Cases study.

Case	PV generation (18MWp)	Batteries (15MWh)	Electricity contract (MW)	Price (\$/MWh)	FEP_1 (\$/MWh)
I			0.635	32.020	33.300
II	✓	✓	0.635	32.020	33.300
III	✓	✓	0.635	32.020	36.120

Note that the model in (27)–(28) and (30)–(35) is a mixed-integer linear programming problem.

III. CASE STUDY

To validate the effectiveness of the contracting strategy proposed, a case study of a consumer with DERs has been considered. The proposed model was implemented in AMPL [23] and solved via the solver IPOPT [24] for the first and second stages, and the solver CPLEX [25] for the third and fourth stages, using a computer with an Intel I5 processor. The consumption data refers to the University of Campinas – UNICAMP in 2019. The UNICAMP has 34,000 students matriculated in 66 undergraduate courses and 153 graduate programs. The electrical system is connected in 138 kV with a contracted power demand of 21.800 MW, totaling around 70 GWh of electricity consumption in 2019. The solar radiation index in the UNICAMP region was defined using the data from the solar photovoltaic plant inside the campus in the same year, with 534 kWp of power generation installed. Both the consumption and generation data were collected at 5-minute intervals and integrated into a one-hour period, totaling 105,120 measurements for the consumption and the same quantity for the generation.

The choice of the representative days of consumption and the solar radiation index were defined using hierarchical grouping [26], implementing in the Matlab the Ward linkage method and using the dendrogram function [27]. In both cases, the measures were clustered in three different days with 24 hours each, and a time interval of $1h$, and taking into account solar irradiation profiles related to sunny and cloudy days typically of one year. Three days were chosen to represent the whole year in order to reduce the computational effort; the difference of the results with more clusters is negligible [22], and there is good adherence of the clusters to consumption and solar radiation behavior. Figure 3 and Figure 4 show the curves of each representative day of consumption and the solar radiation index, respectively. Note that Days 1 represent both the maximum curve of consumption and the solar radiation index, while Days 2 represent the average measures and Days 3 the low measures. The probabilities of the occurrence of each representative day are shown in Table 2. It is important to observe the need to realize the combinations of consumption and solar radiation index probabilities, resulting in nine different probabilities.

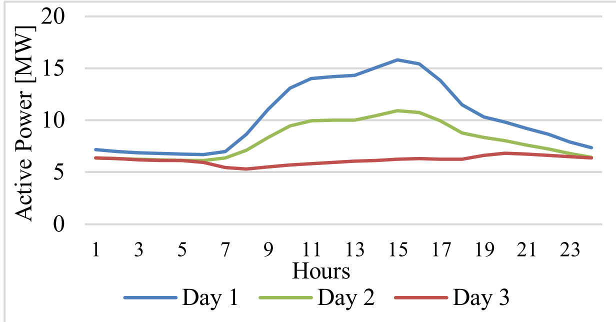

FIGURE 3. Consumption behavior of representative days.

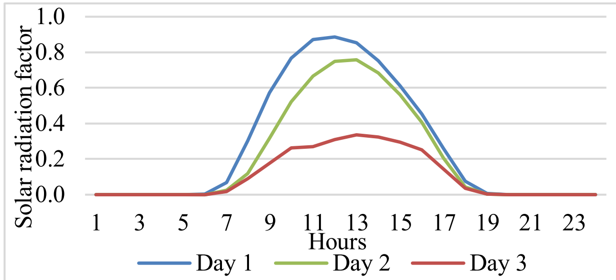

FIGURE 4. Solar radiation factor behavior of representative days.

Table 3 summarizes the case studies considered for the contracting strategy proposed. Case I considers a consumer without renewable generation and batteries; Case II considers a consumer with a solar photovoltaic generation of 18 MWp and a battery system of 15 MWh, and Case III considers the Case II with a FEP of \$36.12/MWh. The market prices were arbitrarily chosen with respect to the range of Brazilian spot electricity prices [28]. Note that the tests consider only one year in advance; nevertheless, the model can consider how many years.

IV. TEST AND RESULST

A. RESULTS CASE I

In this test, the consumer only had a conventional load in its electrical system, and for the next year, the load index considered was increasing by 3.0%. The operational behavior is shown in Figure 5. Note that the active power is higher during the day and lower at night, showing the typical behavior of the consumption.

Figure 6 represents the monthly curves of the contracts, and Table 4 shows the main results of the model. According to the strategy prices of the first year of the contract, the average price needs to be 25.0% lower than the current price; the model found a better price of \$33.200/MWh. Therefore, it is possible to meet the requirement of total consumption with a new contract. For the next year, the total average amount of energy is 7.664 MW, observing the lower and upper limits of seasonality and flexibility in Table 4.

Observe, that, in Figure 6, without the definition of seasonality and flexibility (green curve), the consumer, in the first month, might need to buy 822.268 MWh to meet the total consumption. And in month 6, there would be an excess of 835.583 MWh. For both cases, the consumer would assume

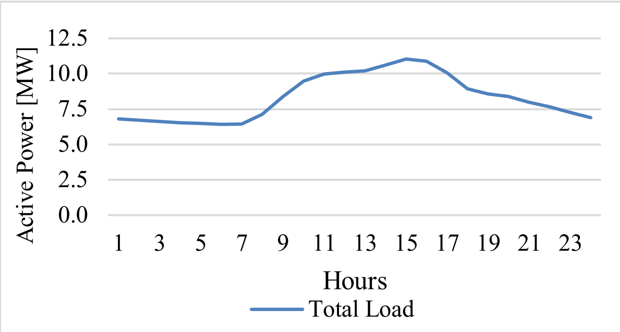

FIGURE 5. Operation behavior of Case I.

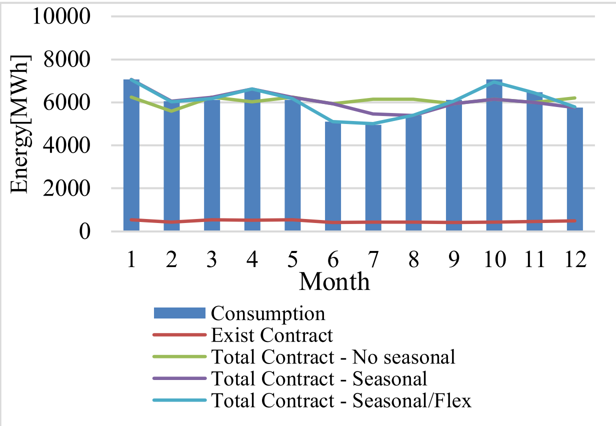

FIGURE 6. Consumption and contracts curves of Case I.

TABLE 4. Results of Case I.

Item	Unit	Value
Average Consumption	MW	8.318
Average Future Contract	MW	7.664
Average Exposure	MW	0.000
Average Price	$/MWh	33.200
	Lower limit	**Upper limit**
Seasonality	-16.0%	14.4%
Flexibility	-15.0%	15.0%

the risks of the spot electricity market. When the flexibility and seasonality are aggregated with the correct strategy of contracting, the exposition, in each month, is insignificant, which brings more confidence to the consumer.

B. RESULTS CASE II

In this test, the DERs were considered and maintained 3.0% of the load index for the next year. Here, there are a photovoltaic generation and batteries available throughout the 24 hours/day. The objective of the operation is to charge the batteries when there is an excess of electricity, from the PV generation being greater than the internal load, and discharge the energy of the battery when the main grid is the supplier, minimizing the electricity purchase by the consumer.

The Figure 7 shows this operational behavior. Note that, at $10h - 14h$, the photovoltaic generation is greater than the internal load consequently, in these moments, the batteries

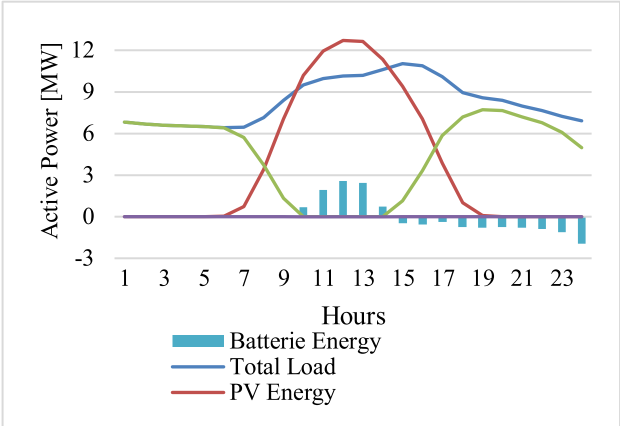

FIGURE 7. Operational behavior of Case II.

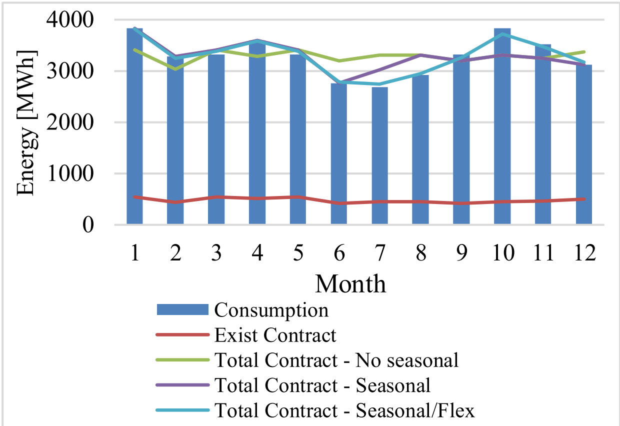

FIGURE 8. Consumption and contracts curves of Case II.

TABLE 5. Results of Case II.

Item	Unit	Value
Average Consumption	MW	4.509
Average Future Contract	MW	3.855
Average Exposure	MW	0.000
Average Price	$/MWh	33.110
	Lower limit	**Upper limit**
Seasonality	-15.4%	14.6%
Flexibility	-12.9%	14.2%

initialize charging.However, the rest hours of the day occur when the internal power demand is greater than the generation; at the time, power is injected into the batteries, softening the internal load curve and reducing the requirement of energy from the main grid. The results of the contracting strategy in this case can be observed in Table 5 and Figure 8. The flat average consumption is 4.509 MW, which is lower than in Case I. In this case, considering the same price strategy in Case I, the model does not return significant exposure; therefore, the future and existing contracts meet the total consumption. The exposure and excess of electricity in months 1 and 6, respectively, are also observed in Figure 8, when seasonality and flexibility are not considered. In this case, the consumer would need to buy 419.940 MWh and sell 428.519 MWh in the spot electricity market. Here, it is

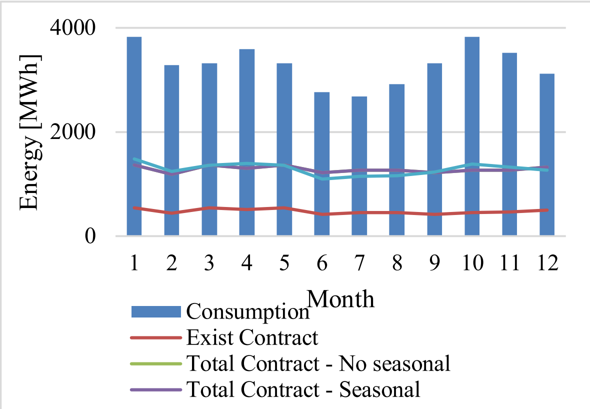

FIGURE 9. Consumption and contracts curves of Case III.

TABLE 6. Results of case III.

Item	Unit	Value
Average Consumption	MW	4.509
Average Future Contract	MW	1.106
Average Exposure	MW	2.750
Average Price	$/MWh	34.590

	Lower limit	
Seasonality	0.0%	0.0%
Flexibility	-14.8%	14.2%

clear that DERs operations not only help to reduce the necessity of selling and buying electricity, but also reduce the total consumption from the main grid by 45.8% and reduce the need for contracting (future contract plus exposure) by 49.7%, compared with Case I. Moreover, when aggregating the seasonality and flexibility required in the contracts, the risks, in the market, are even smaller. It is important to observe the ranges of seasonality and flexibility in Case II. The range of the seasonality is 30%, and of the flexibility is 27.1%. Compared with Case I, which presents 30.4% and 30% respectively, Case II requires a lower financial risk from the supplier, which present the possibility of negotiating better prices.

C. RESULTS CASE III

The last case for this model considered a system similar to Case II, but using a different future price, in order to verify the changes in results in the contracts. The operational results for this case follow the same values of Case II. The results of the contracting strategy for this case are given by Figure 9 and Table 6. The total average flat consumption is 4.509 MW and, different from what was observed in the previous cases, here, there is exposure, since, the model returns the limit of the average price, $34.590/MWh, and neither the future nor the existing contracts are enough to meet the total consumption, as shown in Figure 9. In this case, the average exposure is 2.750 MW. Considering the future price, as shown in Table 3, this model suggests the contracting of 1.106 MW at the moment of the analysis. For the remaining of consumption, the consumer can wait, if possible, the new prices profile of the electricity market, therefore, realize the tests again. Compared with Case II, the average price increased by 4.5%.

The future contract does not be seasonal, in all the months, due to the fact that there is the need to buy more electricity. Thus, there is no reason to realize the balance between deficit and excess, if only deficit exist. It is also important to mention flexibility: here, this requirement of the contract minimizes the deficit for each month.

V. CONCLUSION

A mathematical modeling developed in four different stages has been proposed here to define an optimal electricity contracting strategy for the liberalized market. Hence, this mathematical proposal can be implemented by consumers with or without distributed energy resources (DERs) and, moreover, can help them to reach optimal operation. The results suggest that DERs, such as photovoltaic generation and the battery energy storage system (BESS) improve the exchange of energy in the system by using sustainable energy, since in case that the system requires energy from the main grid, the energy stored in the BESS can be injected into the electrical system, softening the internal power demand and, consequently, reducing the electricity purchase from the main grid.

Moreover, numerical results demonstrated that, depending on the strategy pricing defined and the prices considered, at the moment of the analyses, the consumer can buy all or part of the electricity requirement, thereby preventing the consumer from taking unnecessary risks in the electricity market, taking into account the seasonality and flexibility definitions. Therefore, the model allows for recommendations about the electricity contractual requirements to be made to the consumer, such as the total amount of electricity, average price of the contract portfolio, the exposure in the market, seasonality, and flexibility.

Due to the volatility of price, the smallest exposure to the spot market mitigates the risks. Flat contracts tend not to absorb the variabilities of consumption, but seasonality and flexibility are good requirements to incorporate into contract; indeed, the DERs benefit from seasonality and flexibility when they are applicable.

For future works, the authors intend to implement the contracting strategy considering the sale of electricity, in the spot electricity market, as a resource for improving the financial results of the consumers, moreover, to apply the contracting strategy modeling for the optimal operation of microgrids. Another aspect that can be implemented is to convert this modeling into a user-friendly tool for which consumers can simulate the contracting strategies.

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